Spatiotemporal evolution of carbon emission intensity and the driving effect of green technology innovation: Evidence from China

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Abstract

The "double carbon" goal has proposed new "green" requirements for China's low-carbon economic development, and green technology innovation (GTI) has become an important way to coordinate economic and sustainable development. The study explores the spatial-temporal evolution of carbon emission intensity (CEI) of Chinese prefecture-level cities, analyses the nonlinear impact of GTI on the CEI by constructing a panel quantile model, and draws the following conclusions. First, CEI shows a decreasing trend from 2006 to 2019 and a spatial distribution pattern of "high in the north and low in the south, high in the west and low in the east". Second, GTI significantly reduces CEI, and as the quantile point increases, the carbon reduction effect of GTI is characterized by a U-shaped change, decreasing first and then increasing. Overall, GTI has a significantly more profound inhibiting effect on high CEI regions than on low CEI regions. Third, there is spatial heterogeneity in the impact of GTI on CEI across the four major regions and diverse policy contexts. The study proposes countermeasures for low-carbon development in terms of tapping the potential of GTI, strengthening its regional synergy, and applying locally appropriate measures, to gain the great practical significance for achieving the double carbon target.

Keywords Green technology innovation · Carbon emission intensity · Panel quantile model · Kernel density · The Gini coefficient · The Thiel index · The STIRPAT model

Introduction

As the world's second-largest economy, China is facing serious environmental problems while transforming and upgrading its economic structure. According to the International Energy Agency (IEA) statistics, China is the world's largest emitter of carbon dioxide, with 10081.34 Mt emitted in 2020. The Carbon Accounting Database (CEADs) divides China's carbon emissions into two stages, rapid growth and slow growth, using 2013 as the cut-off point, with the growth rate declining significantly after 2013. In the face of the increasingly challenging environmental state, the Chinese government has proposed carbon peaking and carbon neutrality goals in an initiative to contribute to the world's carbon reduction efforts. Considering the Bulletin

of the State of Eco-Environment in China 2021, 121 out of 339 cities at the prefecture level and above would have exceeded the ambient air quality standard, a decrease of 3.5 percentage points compared to 2020, leading to an urgency to resolve the problem of urban carbon emission reduction. Due to the inertia of economic development and the traditional energy consumption structure, China is characterized by the "high energy consumption, high emissions and high pollution" approach to economic development (Zhang and Liu 2022) and the traditional coal-based fossil energy consumption structure (Xu and Lin 2019). China's carbon emissions have been among the highest in the world (Wang et al. 2016a), making the task of carbon emission reduction a daunting effort.

Green technology innovation (GTI) is an important way to alleviate environmental pressure (Zhu et al. 2020) and is an inevitable choice for China's economy to achieve high-quality development in the new era. The Action Plan for Achieving Carbon Peaks by 2030 explicitly proposes to promote green and low-carbon technological innovation and to advance carbon peaks in an orderly manner. The achievement of the double carbon target relies on the

two main routes of "carbon reduction" and "carbon sink". "Carbon reduction" is particularly important given that "carbon sink" has relatively fixed resources and a time lag. GTI is an important pathway for carbon reduction. This pathway combines new energy development, recycling technology, carbon capture, utilization and storage (CCUS), etc., to promote low-carbon industrial development and the harmonious coexistence of humans and nature. The number of green patent applications in China increased from 19793 in 2006 to 425652 in 2019, with an average annual growth rate of 26.6%. GTI has gradually become a core driving force in promoting high-quality economic and social development. During the transition period of the industrial structure and energy consumption structure, GTI has become the key to achieving economic growth and sustainable development with the premise of ensuring national economic output and economic efficiency (Li and Lin 2017; Wang et al. 2016b).

Influenced by economic development status, GTI has a greater influence on carbon productivity in high-income economies (Du and Li 2019), highlighting the vital role of economic development in GTI for carbon reduction. In addition, research continues to demonstrate that environmental regulation, carbon, and trading green finance are also crucial drivers of GTI to reduce CO_2 emissions (Chang et al. 2023; Huang et al. 2023; Zhang et al. 2022). Integrating GTI resources, bringing into play the spillover effects, and empowering cities to develop green, have become an important path to promote the achievement of the dual carbon goal.

While national strategic plans like the Action Plan to Reach Carbon Peaks by 2030 continue to clarify the importance of technological innovation in China's carbon emission reduction, is the carbon emission reduction effect of GTI consistent across different economic and social conditions and within different scales of geographical units? What is the relationship between GTI and CEI under spatial heterogeneity? What is the impact of GTI on CEI? Can it really contribute to the dual carbon initiatives? The investigation of the effects of GTI on CEI at the prefecture-level city scale provides theoretical support for technology-led carbon peaking and carbon neutral actions and is of great practical significance for carbon reduction actions.

This paper is structured as follows. Section 2 outlines the literature review. Section 3 presents the mechanism analysis. Section 4 describes the research methodology and data sources. Section 5 and Section 6 report the study's results, including the time-spatial evolution analysis, panel quantile model results and heterogeneity results across four regions and various institutional conditions. Section 7 introduces the conclusion and implications.

Literature review

Carbon emission intensity (CEI) is one of the representative indicators for measuring regional carbon emissions (Zhao et al. 2012; Wang and Zheng 2021), and it is better indicator at revealing the ability to carry out sustainable economic and environmental development (Amri 2018). Current intensely researched areas on CEI focus on the following three aspects. First, various regional scales and types of CEI studies should be conducted (Bi and Zeng 2019; Zeng et al. 2022). Focusing on regional research scales such as provincial (Wang and Zheng 2021), urban agglomerations (Yu et al. 2022a) and specific regions (Wang and Zhu 2016) involves research areas such as agricultural carbon emissions (Pang et al. 2020; Zhong et al. 2022), industrial carbon emissions (Yu et al. 2018), and transportation carbon emissions (Chang and Lai 2013). Second, research is conducted on the spatial differences and spatial-temporal evolution of CEI. The spatial variation and spatial correlation of CEI are measured using the Thiel index, coefficient of variation, and Moran's *I* (Wang et al. 2020; Wu et al. 2021), the Markov transfer matrix (Wen and Huang 2019; Wang and Zhu 2016) and the kernel density estimation method (Ke et al. 2022) are used to reveal the spatial and temporal evolution characteristics of CEI. Third, scholars analyse and study the factors that influence CEI. The STIRPAT model, IPAT model, LMDI model, and the spatial econometric model are mainly used to study the influence of economic growth (Zhang et al. 2014; Sun et al. 2021), industrial structure (Lin and Zhu 2017), foreign investment (Cai et al. 2021; Wang and Wang 2021), and population density (Song et al. 2020; Yu et al. 2022; Wen and Huang 2019; Pan et al. 2022) on CEI (Wu et al. 2021; Wang et al. 2015).

In contrast to traditional technological innovation, GTI emphasizes the reduction in undesired outputs like carbon emissions and environmental pollution in the economic production process. Based on this, most scholars consider technological innovations in improving energy use efficiency, reducing pollutant emissions, and developing new energy sources as GTI (Yu et al. 2022c). In recent years, scholars have conducted various studies on GTI. One study involving a discussion of the factors influencing GTI, with the relationship between environmental regulation and GTI being further researched (Zhang et al. 2020). In addition, the influence of aspects such as green finance (Ren et al. 2020), the digital economy (Dong et al. 2022b), and economic development (Wang et al. 2021) on GTI has been deeply explored. Second, research on the efficiency of GTI is carried out mainly from the perspective of the green technology innovation efficiency evaluation and the relevant influencing factors. For example, Dong et al. used

the superefficiency SBM-DEA model to evaluate the efficiency of GTI in the Central Plains urban agglomeration and used the spatial Durbin model to measure the impact of economic development on GTI (Dong et al. 2022c). Third, there is research on the effect of GTI. Most scholars discuss the important role of GTI in accelerating low-carbon transition (Xu et al. 2022a), promoting new urbanization construction (Xu et al. 2022b), promoting pollution and carbon reduction (Xia 2022), and suppressing the ecological footprint (You et al. 2022) around economic effects, social effects, and ecological effects.

As the resource and environmental effects of GTI continue to be highlighted, the relationship between it and CEI has become a research topic of high interest. GTI broadly impacts CEI through the rebound effect, environmental spillover effect, lock-in effect, and compliance cost effect (Sun 2022). Based on this, the current relationship between GTI and CEI is mainly manifested in the following aspects. First, GTI achieves the goal of carbon emission reduction through measures such as improving energy use efficiency and developing alternative energy sources. For example, Zhou et al. argued that the drive for technological progress is an important means to reduce carbon emissions (Zhou et al. 2018; Dong et al. 2022a). Jiao et al. used the STIRPAT model to find that GTI has a significant inhibitory effect on CEI (Jiao et al. 2020). Yu et al. used the mediating effect model to find that GTI and carbon emission trading pilot policies in 281 prefecture-level cities in China jointly reduced CEI (Yu and Luo 2022). Ding et al. used a spatial econometric model to analyse the inhibitory effects of economic development, technological innovation, and foreign investment on CEI in the Yangtze River Basin provinces (Ding et al. 2019). Behera further demonstrated that in 18 emerging countries, GTI did not show a monotonic reduction in carbon emissions in the short and long term but rather a U-shaped relationship (Behera et al. 2023). Second, GTI stimulates further improvements in labour productivity while improving energy use efficiency and saving production costs for enterprises, expanding the economic scale of these enterprises, increasing energy demand and increasing carbon emissions. Hao et al. used dynamic threshold panel regression to find that the interaction of international technology spillover and intellectual property protection significantly increased carbon emissions in eastern and central China (Hao et al. 2021). Zheng et al. used the DEA-Malmquist method to suggest that technological progress increases CEI (Zheng et al. 2022). Third, the relationship between GTI and carbon emissions is uncertain due to the rebound effect. This is evidenced by the study of Chen et al. who found a nonlinear inverted U-shaped relationship between GTI and carbon emissions in China's provincial areas, with GTI reaching a certain level before it suppresses carbon emissions (Chen

et al. 2023), Liang et al. found a U-shaped relationship between GTI and carbon emissions in the logistics industry (Liang et al. 2022).

Generally, current studies have ignored the regional spatial variability of the carbon emission reduction effect of GTI and instead concentrated on the overall study of GTI at the macro scale. The following are some of this paper's significant contributions. Firstly, China has a sizable geographical area, and because location factors have a substantial impact on regional disparities, GTI and CEI levels are spatially non-homogeneous. From the standpoint of geographical non-homogeneity, the study ingeniously investigates the carbon emission reduction effect of GTI at the prefecture-level city size. Secondly, as there is no uniform conclusion on the connection between GTI and CEI, the study expands on its investigation of the nonlinear relationship between GTI and CEI in the four major regions of eastern, central, western, and northeastern China. It also examines whether GTI exhibits monotonic reduction in cities with various CEI in the four major regions. It considers whether the empirical findings from emerging economies are equally applicable in China? Thirdly, considering China's unique institutions, the panel quantile model is further combined with institutional factors like marketization level and environmental regulations to deepen the regional variability of the carbon emission reduction effect of institutional factors. Exploring the carbon reduction effect of GTI under the condition of spatial heterogeneity is vital for precise carbon reduction and promoting the laddering of carbon peaking in various regions.

Based on the above background, this study explores the spatial and temporal evolution characteristics of CEI by using kernel density estimation, the Gini coefficient and the Thiel index in 264 prefecture-level cities and studies the spatial heterogeneity of GTI on CEI in different regions by using a panel quantile model. Furthermore, the study provides targeted policy suggestions in terms of tapping the potential of GTI, strengthening the synergy of regional GTI, and tailoring policies to local conditions, with a view to providing lessons for achieving regional synergy in emission reduction and dual carbon targets.

Mechanism analysis

The complex mechanism of the influence of GTI on CEI is shown in Figure 1 and can be summarized into two realization paths, energy structure and industrial structure, two mechanisms of action, spillover effect and rebound effect, and two forms of influence, direct and indirect. From the perspective of the realization path, the vigorous implementation of national new energy policies and green financial policies, on the one hand, provides policy support and

Fig. 1 The GTI and CEI impact mechanism map
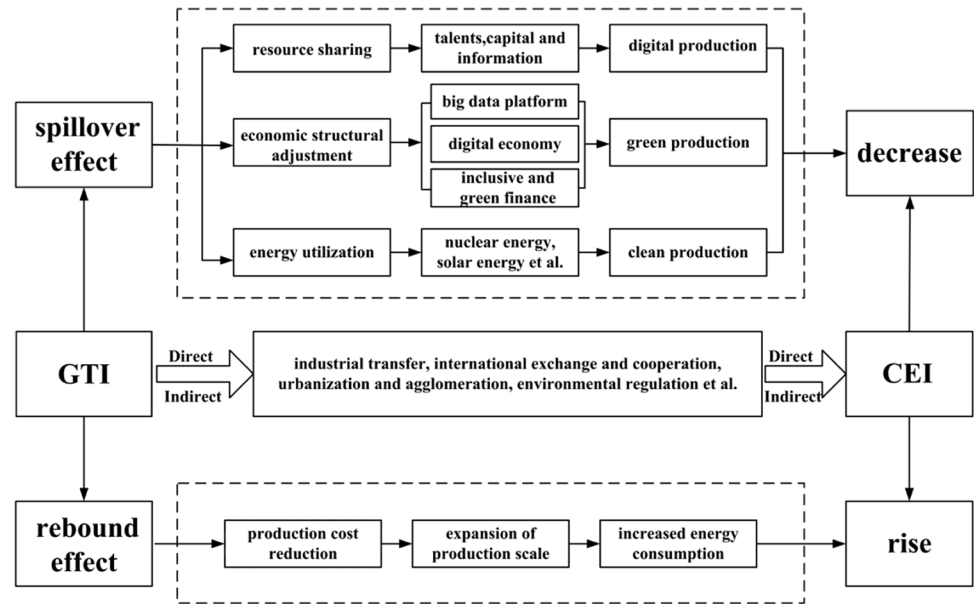
financial guarantees for low carbon development, boosts the development and utilization of alternative clean energy and renewable energy such as nuclear power, hydropower, wind power, geothermal energy and tidal energy, reduces the consumption of traditional fossil energy such as coal and oil, optimizes the energy allocation structure and reduces carbon emissions. On the other hand, it promotes the development of low-carbon technologies such as carbon capture and storage technology, new materials and circular economy, eliminates backwards production capacity in key industries and key areas, helps advance, rationalize and clean the industrial structure, and helps achieve carbon emission reduction. In terms of the mechanism of action, under the influence of government environmental regulation and market-based instruments such as the carbon emission trading market, the Porter hypothesis has to some extent stimulated the improvement of GTI capacity in high-carbon emission industries, realized interindustry, interregional and international sharing of talents, resources and information through technology spillover effects, relied on big data, the digital economy and green finance, and promoted industries to achieve digital, green and clean production. This will change the low-end locking status of industries, promote the reasonable concentration and flow of capital, technology, population and other factors, and promote the advanced industrial structure while improving energy utilization efficiency and achieving carbon emission reduction. As GTI further develops, the production costs of enterprises keeps decreasing, the price of products keeps falling, the market demand further expands, and enterprises expand the scale of production and consume more energy in pursuit of profits, at which time the rebound effect of GTI becomes prominent (Cheng et al. 2023), the energy demand brought by GTI becomes greater than the

energy savings, and the CEI starts rising. In terms of influence forms, GTI can directly or indirectly affect carbon emissions through industrial structure upgrading, industrial transfer, energy use, international exchange and cooperation, urbanization and agglomeration, and environmental regulation, causing changes in CEI.

Methods and data

Methods

Gini coefficient and Thiel index

The Gini coefficient is usually used to portray the regional development disparity of geographical items, and it takes values in the range of [0,1]. The larger the Gini coefficient is, the greater the degree of regional differences in CEI, the smaller the Gini coefficient is, the smaller the degree of regional differences in CEI.

$$G = \left(2 \sum_{i=1}^{n} i \cdot X_i \right) / \left(m^2 \cdot u_x \right) - (m+1)/m \qquad (1)$$

G represents the Gini coefficient of CEI; m represents the number of study samples; X_i represents the CEI of prefecture−level city i; u_x represents the average value of CEI; i represents the ranking according to the size of CEI.

The Thiel index is introduced to measure the regional balance of CEI, whereby the range of the index is [-1,1], and when the absolute value of the Thiel index is closer to 1, it indicates that the balance of CEI between regions is lower, whereas the smaller the Thiel index is, that is, if the

absolute value is closer to 0, it indicates that the balance of CEI between regions is higher.

$$T = \frac{1}{n} \sum_{i=1}^{n} \frac{y_i}{\bar{y}} \log\left(\frac{y_i}{\bar{y}}\right) \qquad (2)$$

T denotes the Thiel index of CEI; n denotes the number of study samples; y_i denotes the CEI of prefecture−level city i; $\bar{y}$ denotes the average value of CEI.

Spatial autocorrelation analysis

The Moran's I is often used in spatial correlation analysis. The Moran's I can be divided into a global Moran's I and a local Moran's I. In this paper, the global Moran's I is used to analyse the spatial agglomeration of the national CEI.

$$Moran's\ I = \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \qquad (3)$$

N represents the prefecture-level cities in China; y_i represents the CEI of city i; $\bar{y}$ represents the CEI; W represents the spatial weighting matrix. The Moran's I range is [-1,1], with positive values representing positive spatial autocorrelation and negative values representing negative spatial autocorrelation of CEI.

The STIRPAT model

The STIRPAT model is a development of the IPAT model, which has the following basic form:

$$I = a\,P^b A^c T^d e \qquad (4)$$

I, P, A and T represent regional CEI, population density, economic development level and GTI ability, respectively; a denotes the model coefficient; b, c and d denote the variables for population, economic development level and technical factors, respectively; and e denotes the model error term.

The baseline regression and the panel quantile model

To examine the relationship between GTI and CEI in the eastern, central, western and northeastern regions, the following baseline regression model was set:

$$\ln CEI_{it} = \beta_0 + \beta_1 \ln GTP_{it} + X'_{it}\beta + \mu_i + \delta_t + \varepsilon_{it} \qquad (5)$$

$\ln CEI_{it}$ denotes the CEI of the explanatory variable. i denotes the prefecture-level city. t denotes the year. X'_{it}

denotes the control variable. μ_i denotes individual fixed effects. δ_t denotes time fixed effects. ε_{it} denotes the random disturbance term.

The vast majority of regression models have been developed from ordinary least squares (OLS), a model that can only measure the effect of the independent variable on the conditional mean of the dependent variable but does not reflect the full picture of the entire conditional distribution of the dependent variable and therefore does not reflect the heterogeneity of factors influencing CEI across regions. To compensate for the shortcomings of OLS, as it is highly susceptible to extreme values, Koenker et al. (Koenker 2004) proposed the quantile regression model, taking the following general form:

$$Q_\tau(y_i) = \beta_0(\tau) + \beta_1(\tau)x_{i1} + \cdots + \beta_p(\tau)x_{ip} \qquad (6)$$

The study decomposes the factors influencing CEI based on the STIRPAT model (Wen and Shao 2019) and constructs the following panel quantile model.

$$Q_\tau \ln CEI_i = \beta_0(\tau) + \beta_1(\tau)\ln GTI_{i1} + \beta_2(\tau)\ln PGDP_{i2} + \beta_3(\tau)\ln IS_{i3} + \beta_4(\tau)\ln FDI_{i4} + \beta_5(\tau)\ln PD_{i5} + \varepsilon \qquad (7)$$

τ denotes the quantile point, $Q_\tau \ln CEI_i$ denotes the τ conditional quantile result for CEI, β_i is the regression coefficient of the explanatory variable at the quantile point, GTI denotes green technology innovation, $PGDP$ denotes the level of economic development, IS denotes industrial structure, FDI denotes the level of external openness, and PD denotes population density. ε denotes the random error term, and β_0 is the intercept term. To reduce the errors caused by heteroskedasticity and differences in magnitudes, all variables are normalized and treated logarithmically.

Data

Explained variable

Carbon emission intensity (CEI), carbon emissions per unit of GDP, is an important indicator of economic and environmental sustainability (Dong et al. 2018; Zhao et al. 2022). The calculation of carbon emissions is based on the Cheng et al. approach (Cheng et al. 2023).

Core explanatory variables

The measurement of GTI includes the perspectives of measuring the efficiency of GTI and measuring the output of green patents. Compared with the former, green patents are more intuitive and quantifiable, and data are available at the prefectural level. Because of the lag in the granting of patents and the difference between GTI and traditional technology innovation, the use of patent grants (Lee and

Table 1 Description of each factor variable

Variables	Symbol	Definition
Carbon emission intensity	CEI	Carbon emissions/GDP
Green technology innovation	GTI	Number of green invention patent applications+Number of green utility model patent applications
Level of economic development	PGDP	Real GDP per capita
Level of openness to the outside world	FDI	Actual foreign investment/GDP
Industrial structure	IS	Value added of secondary industry/GDP
Population density	PD	Total population/administrative area

Table 2 Variable descriptive statistics

Variables	Obs	Mean	S. D.	Min	Max
lnCEI	3696	-1.1052	0.7738	-3.7832	2.2568
lnGTI	3696	4.6515	1.8560	0	10.4536
lnPGDP	3696	10.4460	0.6963	4.5951	13.0557
lnIS	3696	3.8409	0.2439	2.4596	4.4497
lnFDI	3696	0.0581	1.3258	-8.6393	3.0448
lnPD	3696	5.7802	0.9124	1.5476	7.9227

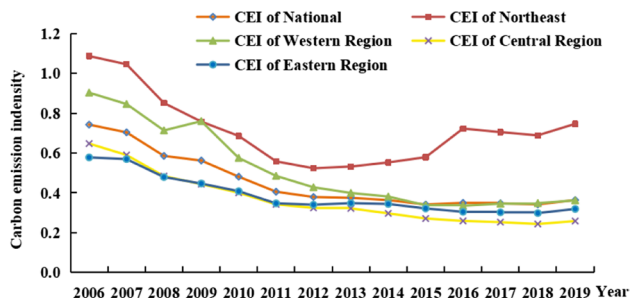**Fig. 2** Trends in the temporal evolution of CEI in China and the four major regions

Lee 2013), patent inventions (Lin and Du 2015) and research expenditure ratios (Irandoust 2016) to measure GTI may be somewhat inaccurate. The research obtained information on all patent applications published by the National Intellectual Property Administration (Dong et al. 2020) based on the Green List of the International Patent Classification launched by the World Intellectual Property Organization (WIPO) and selected the number of green invention patent applications and green utility model patent applications to represent GTI by referring to Weng et al. (Weng et al. 2022).

Control variables

In addition to GTI, the study chose the four aspects in Table 1, namely, the level of economic development, industrial structure, openness to the outside world and population density, as explanatory variables to analyse the relationship between each factor and CEI.

Data source

Based on the availability of data, prefecture-level cities with serious missing data were removed, and some of the missing data were linearly interpolated. Finally, data from 264 prefecture-level cities in China from 2006-2019 were selected for analysis, accounting for the influence of prefecture-level city divisions. All data were obtained from the *China Urban Statistical Yearbook*, *China Statistical Yearbook*, prefecture-level municipalities' statistical yearbooks and statistical

bulletins. The descriptive statistics for all variables are presented in Table 2.

According to the National Bureau of Statistics division method, the 264 prefecture-level cities are divided into four regions: eastern region, central region, western region and northeastern region. The prefecture-level cities in 10 provinces, including Beijing, Tianjin, Shanghai and so on, are part of the eastern region. The six prefecture-level cities in Shanxi, Anhui, Henan and other provinces are in the central region. The prefecture-level cities in 12 provinces (autonomous prefectures), including Chongqing, Sichuan and Yunnan, belong to the western region. And the prefecture-level cities in three provinces, Liaoning, Jilin and Heilongjiang, belong to the northeastern region.

Empirical results

Time evolution of CEI

From 2006 to 2019, the average CEI in China showed a decreasing trend each year, as it decreased from 0.74 tons per million yuan in 2006 to 0.36 tons per million yuan in 2019, with an average annual decrease rate of 5.39% as shown in Figure 2. From 2006 to 2019, the CEI of the northeast region showed a U-shaped trend and was always higher than the national average CEI by region. From 2006 to 2019, the CEI of the western region fluctuated and decreased, and

after 2015, it was close to the national average level. This may be related to the construction of "low-carbon pilot cities" and "national ecological civilization demonstration zones". On the one hand, green finance and carbon trading have contributed to the rapid development of low-carbon and clean technologies in the western region, and industrial production tended to be advanced and clean. On the other hand, clean energy resources such as wind and solar energy have been fully developed in the western region, and the energy consumption structure has significantly improved. The central and eastern regions have always been lower than the national average CEI, approximately showing that the central region > the eastern region from 2006 to 2008, the central region and the eastern region were similar in CEI from 2009 to 2012, and the central region < the eastern region from 2013 to 2019. The 2006 carbon emission intensities of the eastern region and the central region were 0.578 and 0.647, respectively, and the carbon emission intensities of the two regions in 2019 were 0.578 and 0.647, respectively. The carbon emission intensities of the two regions were 0.319 and 0.259, respectively, and the average annual decline rates were 4.47% and 6.80%, respectively.

From 2006 to 2019, the Gini coefficient and the Thiel index of the CEI of prefecture-level cities in China showed approximately the same fluctuating decreasing and then increasing trend as shown in Table 3. The Gini coefficient and the Thiel index decreased in 2019 compared with 2006, and the regional differences narrowed, which is related to the strengthening of regional synergy and emission reduction, optimization and improvement of energy policies and industrial green transformation.

To further investigate the time-series evolution of CEI, the kernel density curves are plotted for four years in Figure 3: 2006, 2010, 2015 and 2019. From the centre of the curve, the centre of the kernel density curve shifts to the left, the peak increases, and the shape changes from "short and fat" to "tall and thin", indicating that the CEI of Chinese prefecture-level cities decreases year by year and the regional gap decreases. In terms of the tails on both sides, the right
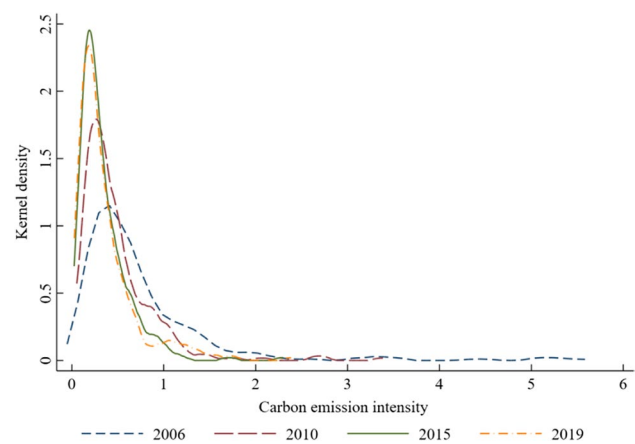

Fig. 3 The kernel density curve of CEI

trailing edge is always longer than the left trailing edge, and the length of the trailing edge decreases, indicating that the CEI of some prefecture-level cities in China is significantly higher than that of other cities, and the number of prefecture-level cities with high CEI decreases significantly.

Spatial evolution of carbon emission intensity

The visualization of the CEI in China from 2006 to 2019 using the ArcGIS natural breakpoint method in Figure 4 shows that the overall CEI indicates a spatial distribution pattern of high in the north and low in the south, high in the west and low in the east, and this is closely related to China's industrial layout, economic development level, energy consumption structure, etc. (Ahmad et al. 2021). In 2006, the lowest CEI was 0.066 in Lincang, and the highest was 5.467 in Xining. In 2019, the lowest was 0.028 in Chongzuo, and the highest was 2.386 in Wuhai. From 2006 to 2019, the CEI decreased significantly, and the number of prefecture-level cities with high CEI decreased significantly. By region, the northwest region has the highest CEI, with the high CEI prefecture-level cities distributed in clusters, while the high CEI prefecture-level cities in the central region are distributed in points and are mainly in resource-based cities. The carbon emission reduction effect of GTI is relatively weak in the two regions because of the heavy industrial structure, relatively slow-paced development mode, need for an improved technology innovation capacity, and insufficient R&D investment. The prefecture-level cities with high CEI in Northeast China are distributed in surface distribution. From the perspective of provinces, the high CEI areas in Liaoning Province form a "C" distribution pattern with Dandong-Benxi-Tieling-Fuxin as the boundary. The overall CEI in Jilin Province is low. The CEI in Heilongjiang Province is high in the north and low in the south, high in the east and low in the west. The prefecture-level city with a high CEI

Table 3 The Gini coefficient and the Thiel index for the CEI of prefecture-level cities in China

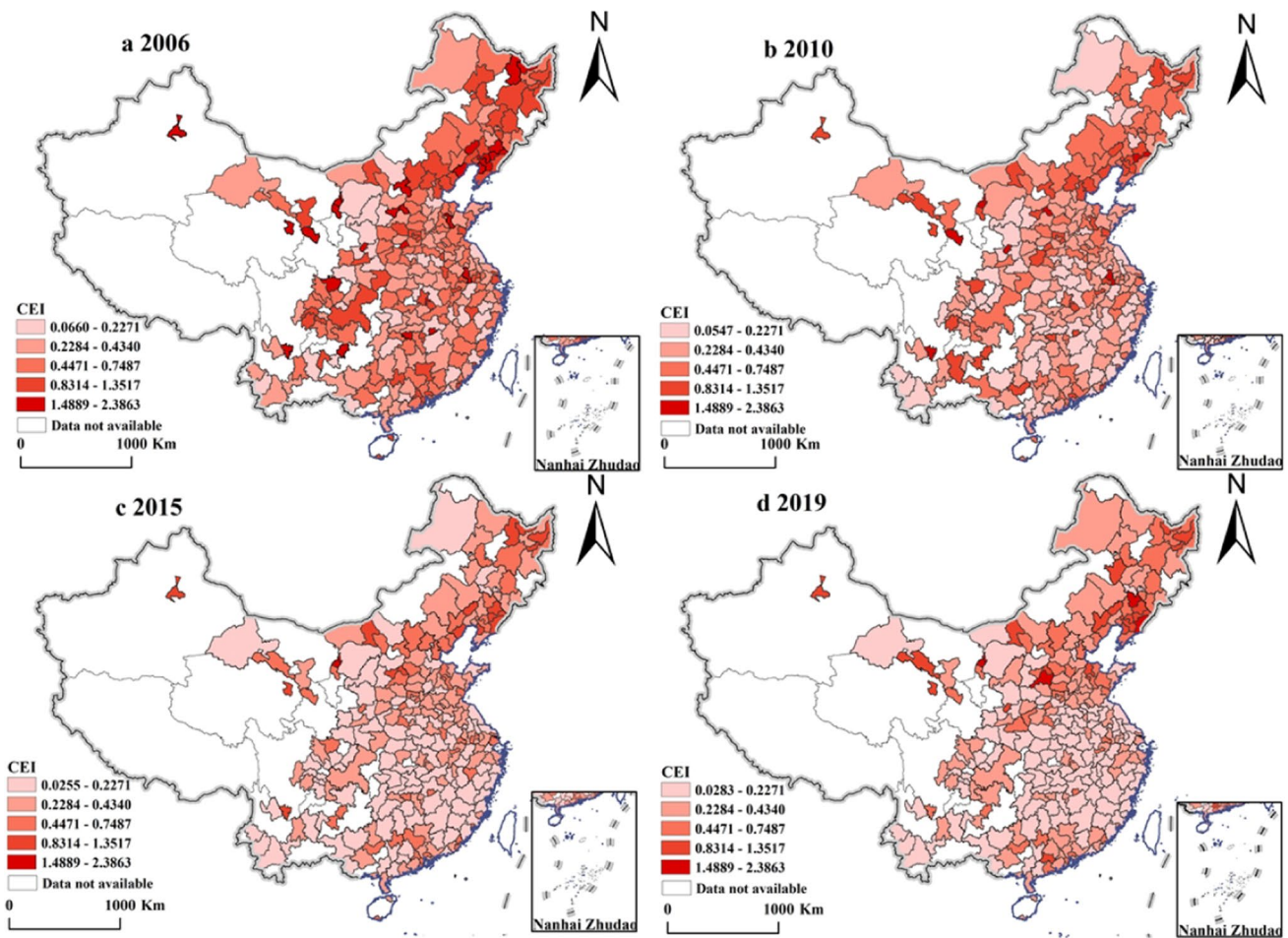| Year	Gini coefficient	Thiel index	Year	Gini coefficient	Thiel index
2006	0.4349	0.1513	2013	0.3656	0.1001
2007	0.4112	0.1311	2014	0.3700	0.1028
2008	0.4121	0.1324	2015	0.3794	0.1057
2009	0.4200	0.1595	2016	0.4070	0.1238
2010	0.3879	0.1145	2017	0.4098	0.1260
2011	0.3817	0.1123	2018	0.4178	0.1317
2012	0.3750	0.1075	2019	0.4308	0.1385

Fig. 4 China's CEI in 2006, 2010, 2015 and 2019

is mainly Hegang in the north. This is mainly related to the shrinkage of cities in the northeast, and thus is affected by the bottleneck of transformation of resource-based cities, the heavy industrial structure of the northeast, the unreasonable allocation of labour resources, the insufficient support capacity of urban development, and the limited level of GTI, restricting the reduction in CEI. The CEI of the eastern region, especially the southeast coastal region south of the Qinling and Huaihe Rivers, is relatively low, and is related to the high level of development of the regional circular economy and low-carbon economy.

Exploratory space analysis of carbon emission intensity

The study measured the CEI Moran's *I* of each prefecture-level city using Geoda software, and the results are in Table 4. The Moran's *I* is positive in all cases and it passes the 1% significance test in all years except 2006, the year in which it passes the 5% significance test. CEI has a significant positive spatial correlation, showing that the

Table 4 Moran's *I* of CEI from 2006 to 2019

Year	CEI	Z	Year	CEI	Z
2006	0.186**	4.0785	2013	0.227***	5.5181
2007	0.188***	4.4904	2014	0.248***	6.6075
2008	0.178***	4.2096	2015	0.304***	7.2384
2009	0.225***	8.6023	2016	0.390***	9.3343
2010	0.217***	5.7006	2017	0.374***	9.2861
2011	0.209***	5.5897	2018	0.350***	8.9791
2012	0.212***	5.4329	2019	0.349***	9.1630

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

CEI of the prefecture-level cities is influenced by the surrounding prefecture-level cities. The Moran's *I* shows a fluctuating upward trend during the study period, reaching the maximum value in 2016, and the spatial agglomeration slightly weakened after 2016.

The results of the panel quantile model

Stability test

To ensure that the data are smooth and valid and to avoid pseudoregression, the variables were tested for smoothness in Table 5, and all variables passed the LLC and ADF tests, and the data were smooth without unit roots.

Panel quantile regression results

To comprehensively and effectively determine the factors influencing CEI and regional differences, the study selected five representative quantiles of q10, q25, q50, q75, and q90 for panel data regression and listed the fixed-effect model as a comparison in Table 6. The coefficient of GTI is negative and passes the 1% significance test in all five quantiles, indicating that GTI is an effective way to reduce carbon emissions. With the increase in the quantile, the carbon emission reduction effect of GTI shows a U-shaped weakening change and then a strengthening change, probably because GTI affects CEI mainly through the technology spillover effect and rebound effect. Moderate environmental regulation significantly promotes the rapid development of GTI and the

improvement of energy use efficiency, enabling enterprises to achieve relatively "clean" production, and playing a positive role in reducing CEI. With the widespread application of GTI, enterprises' production costs have decreased, and product prices have fallen, stimulating greater market demand and highlighting the rebound effect. However, at a comprehensive view, the coefficient of the impact of GTI on CEI is negative, that is, the carbon emission reduction effect of GTI is greater than the carbon emission scale expansion effect brought by its promotion of economic growth, so GTI is an effective way to reduce CEI. In addition, the inhibiting effect of GTI on CEI is significantly better in the higher quantile areas than in the lower quantile areas, and this is mainly related to the foundation of GTI. The lower quantile areas already have had a preliminary green production and living system in resource use, energy substitution, production, waste treatment, transportation and travel, with relatively low pollutant emissions and reduced reliance on GTI. While in the higher quantile areas, there is more room for carbon emission reduction, and GTI further releases technological dividends and helps green and low-carbon transformation.

The regression coefficient of the economic development level is significantly positive. It is thus related to the fact that after economic development reaches a threshold, the industry moves from an "agglomeration economy" to an "agglomeration diseconomy". There is spatial heterogeneity in the regression coefficients of industrial structure, which is negative at q10, q50 and q75 and positive at q25 and q90, and is closely related to the type of regional industries and the way of industrial development. Foreign investment in the middle and low quantile regions follows the pollution refuge hypothesis. It promotes carbon transfer while transferring the three high industries, but in the high quantile regions it follows the pollution halo hypothesis. The spillover of knowledge and technology improves the level of technology management and energy use efficiency in the region, reducing CEI (Wang et al. 2019). Population density

Table 5 Stability test of panel data

Variable	LLC Test		ADF-Fisher Test	
	Stat.	p-Value	Stat.	p-Value
lnCEI	-16.3386	0.0000	18.3703	0.0000
lnGTI	-28.5635	0.0000	24.6594	0.0000
lnPGDP	-15.9628	0.0000	12.7209	0.0000
lnIS	-5.9602	0.0000	20.1192	0.0000
lnFDI	-20.3574	0.0000	22.6654	0.0000
lnPD	-18.5584	0.0000	11.5451	0.0000

Table 6 The panel quantile regression results

Variables	q10	q25	q50	q75	q90	FE
lnGTI	-0.143***	-0.111***	-0.097***	-0.157***	-0.171***	-0.0228**
	(0.0299)	(0.0141)	(0.0145)	(0.0182)	(0.0304)	(0.00962)
lnPGDP	0.376***	0.235***	0.169***	0.244***	0.227***	-0.524***
	(0.0790)	(0.0457)	(0.0385)	(0.0463)	(0.0778)	(0.0221)
lnIS	-0.045	0.033	-0.014	-0.010	0.055	-0.131***
	(0.115)	(0.0959)	(0.0585)	(0.0938)	(0.110)	(0.0434)
lnFDI	0.103***	0.111***	0.089***	0.029*	-0.056***	0.009
	(0.0216)	(0.0132)	(0.0148)	(0.0164)	(0.0169)	(0.00618)
lnPD	0.180***	0.143***	0.048**	0.025	0.017	0.030
	(0.0358)	(0.0194)	(0.0210)	(0.0309)	(0.0359)	(0.0633)
Constant	-6.169***	-4.520***	-2.668***	-2.502***	-2.019***	4.805***
	(0.711)	(0.498)	(0.489)	(0.530)	(0.759)	(0.412)
Observations	3696	3696	3696	3696	3696	3696

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

contributes to CEI, mainly because increasing population density increases energy demand and pollutant emissions.

Heterogeneity analysis

Analysis of spatial heterogeneity

To further illustrate the heterogeneity of the effects of GTI on CEI in the eastern, central, western, and northeastern regions, a panel quantile regression model is used to test the heterogeneity in Table 7. The impact of GTI on CEI in the four major regions is spatially heterogeneous. In the eastern region, the effect of GTI on CEI showes a negative inhibitory effect and the carbon emission reduction effect is enhanced as the quartile increases. With the compensatory effect of GTI and the free flow of green production factors, the financing pressure of the green development of enterprises has been eased, and the rapid development of green and low-carbon technology has pushed forward carbon emission reduction in the eastern region. Overall, the eastern region has a higher level of GTI, a mature innovation system, a diminishing marginal effect, and a reduced dependence on GTI. The middle and lower quartiles in the central region show a negative inhibitory effect at the 1% significance level. The industrial transfer brought along relatively advanced production technologies, releasing the environmental spillover effects of GTI. In the western and the northeast regions, there is spatial heterogeneity in the effects of GTI and CEI. High-quantile areas have a significant negative inhibitory effect, while low-quantile areas have a significant positive promotional effect. Resource-based cities with high carbon emissions, such as Benxi, have continued to adjust their industrial structure and optimize their energy consumption patterns, thus contributing to a reduction in CEI. Strategic plans such as the revitalization of Northeast China and the establishment of the demonstration zone for undertaking industrial transfer in Jixinan have attracted some polluting industries to transfer to low-carbon-emitting cities, coupled with the relatively low level of marketization, the existence of mismatch of innovation resources and other problems, the economic growth effect brought about by technological progress is greater than the emission reduction effect of technological advances.

Analysis of policy context heterogeneity

The study is based on the average of marketization and environmental regulation, with prefecture-level cities that are greater than the average being labeled as high marketization level (H-MI) and loose environmental regulation (L-ER) areas, respectively. On the contrary, they are low marketization level (L-MI) and strict environmental regulation (S-ER) areas. The impacts of GTI on CEI under the four policy conditions of L-MI, H-MI, S-ER and L-ER are denoted as $lnGTI_1$, $lnGTI_2$, $lnGTP_3$ and $lnGTP_4$, respectively (Table 8).

Table 7 Analysis of spatial heterogeneity

Variables	Eastern Region			Central Region			Western Region			Northeast Region		
	q30	q60	q90	q30	q60	q90	q30	q60	q90	q30	q60	q90
lnGTI	-0.055***	-0.059***	-0.061**	-0.124***	-0.223***	-0.231***	0.0834*	-0.070	-0.145***	0.094***	-0.027	-0.111**
	(0.0209)	(0.0133)	(0.0262)	(0.0346)	(0.0180)	(0.0537)	(0.0435)	(0.0567)	(0.0462)	(0.0248)	(0.0329)	(0.0503)
Constant	-1.130	-1.775***	-1.278***	-8.295***	-8.167***	-7.108***	-0.843	-3.521**	-6.285***	1.710**	1.727***	1.004
	(0.772)	(0.656)	(0.635)	(0.817)	(0.507)	(1.260)	(1.247)	(1.669)	(0.872)	(0.783)	(0.662)	(0.676)
Control variable	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1204	1204	1204	1106	1106	1106	924	924	924	462	462	462

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

Table 8 Analysis of heterogeneity of policy context

Variables	q10	q25	q50	q75	q90
$lnGTI_1$	-0.100*** (0.0378)	-0.104*** (0.0237)	-0.087*** (0.0204)	-0.146*** (0.0350)	-0.093*** (0.0311)
$lnGTI_2$	-0.186*** (0.0258)	-0.115*** (0.0198)	-0.100*** (0.0239)	-0.149*** (0.0199)	-0.216*** (0.0279)
$lnGTI_3$	-0.264*** (0.0469)	-0.228*** (0.0591)	-0.240*** (0.0418)	-0.208*** (0.0325)	-0.215*** (0.0209)
$lnGTI_4$	-0.112*** (0.0244)	-0.085*** (0.0130)	-0.046*** (0.0126)	-0.048*** (0.0113)	-0.073*** (0.0246)
Control variable	YES	YES	YES	YES	YES

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

Among them, the environmental regulation is calculated by the entropy weight method to measure industrial wastewater, industrial sulphur dioxide and industrial smoke (dust) emissions per unit of output value, and the marketization level is calculated regarding the National Economic Research Institute.

Overall, the suppression of CEI by GTI is stronger under the conditions of H-MI and S-ER areas. Strict environmental regulations force enterprises to increase investment in GTI, improve production and operation methods, reduce end-of-pipe emissions of pollutants, and promote the recycling of resources, which is a vital and indispensable means to achieve pollution reduction and carbon reduction at this stage. Full free flow of factors in the market, open and transparent market information, efficient matching with the green development needs of enterprises, and the realization of progress in green technologies, green processes and green products, which further reduces carbon emissions. Therefore, the further release of the carbon emission reduction effect of GTI requires the efficient and coordinated development of an active government and an effective market.

Conclusion and implications

Exploring the heterogeneity of the impact of GTI on CEI among Chinese prefectures is of great practical significance and is required to implement differentiated, targeted and specific carbon emission reduction policies to promote the development of a low-carbon and circular economy in China. This paper uses a panel quantile model to measure the nonlinear relationship between GTI and CEI. The following findings were uncovered. First, the CEI of Chinese prefecture-level cities showed a decreasing trend from 2006 to 2019, with spatial distribution characteristics of high in the north and low in the south, high in the west and low in the east, and the spatial gap was narrowed by the influence of regional synergistic emission reduction. Second,

the spillover effect of GTI is stronger than the rebound effect, and thus has a significant inhibitory effect on CEI and shows a U-shaped trend of decreasing and then increasing as the quantile increases. Economic development and population density significantly lead to an increase in CEI, while the effects of foreign direct investment and industrial structure on CEI are heterogeneous. Finally, there is spatial heterogeneity in the impact of GTI on CEI among and within the four major regions and has been verified in different institutional contexts, with a significant inhibitory effect on the eastern regions, the central region, the western and northeast with high CEI regions. Conversely, there is a facilitative effect on the northeast and western with low CEI areas. This is mainly related to the industrial base and the level of technological innovation in each region.

Based on the above conclusions, this paper proposes countermeasure suggestions from the following aspects. First, tap the potential of GTI and release the dividends of GTI. On the one hand, we should increase the investment in green science and technology, reduce the trial-and-error costs of GTI, promote low-carbon, zero-carbon, negative-carbon and other key core technologies, train professional talent in new technology fields, and release its dividends. On the other hand, a leading role should be assumed by carbon peak action through strengthening basic research on new and renewable energy applications, developing alternative new energy sources such as nuclear power and hydropower, and reducing carbon emissions in production and living. Second, strengthen the synergy of regional GTI and promote the synergy of regional pollution and carbon reduction. Establish an international cooperation and exchange system and a regional green innovation network, improve the speed and scale of circulation of GTI, give full play to the comparative advantages of GTI in the eastern region, and enhance inter-regional and intraregional technology exchange links. Third, differentiated policies should be implemented according to local conditions. Differences in geographical conditions lead to various priorities in the development of GTI. The eastern region should give full play to its advantages in green innovation, enhance green innovation exchanges at home and abroad and lead the development of green innovation. The central and western regions should strengthen regional innovation exchanges, improve the rate of transformation of green achievements and release green innovation dividends. And the northeastern region should pay attention to raising the market access threshold while accepting industrial transfer and reduce the transfer of highly polluting industries while introducing advanced production technologies. In addition, the government should reasonably grasp the intensity of environmental regulations, adopt industry-differentiated policies, give full play to the role of the market, promote the free flow of resource factors, and promote technological innovation towards green and low-carbon.

Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent to publish Not applicable.

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